SYNOPSIS REPORT ON

Cardiac Disease Detection Using AIOT

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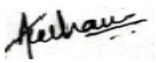
DECLARATION

I hereby declare that, the present work completed in the form of synopsis entitled, "Cardiac Disease Detection Using AIOT" is an original work carried out by me under the guidance of Dr. Jayshri D. Pagare, and has not been submitted or published in any form for the fulfillment of any other degree or any other similarwork to this in other University.

I further declare that the material obtained from other sources has been duly acknowledged in the synopsis.



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CERTIFICATE

This is to certify that Archana H. Telgaonkar has carried out the work embodied in this synopsisentitled "**Cardiac Disease Detection using AIOT"**. The work included in this synopsis is original, unless stated otherwise and has not been submitted for other degree of MGM University or any other University. References made to the work of others have been cited in the text.

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Introduction

Cardiac Disease Detection Using AIOT (Artificial Intelligence & Internet of things)

Cardiovascular diseases remain a leading global health challenge, and timely detection of arrhythmias is critical to reducing associated mortality [1]. This study focuses on developing a comprehensive Artificial Intelligence of Things (AIoT)-based ECG analysis system that integrates wearable sensors, real-time signal acquisition, and hybrid deep learning models for accurate arrhythmia detection and classification.

Arrhythmias refer to irregularities in the heart's normal rhythm, caused by abnormal electrical impulses that regulate the heartbeat. Under normal condition heart rhythm is generally consistent, but in presence of arrhythmias may lead the heart to beat too quickly (tachycardia), too slowly (bradycardia), or in an irregular sequence. While some rhythm disturbances are harmless, others can significantly reduce the heart's pumping efficiency, leading to serious consequences such as stroke, heart failure, or even sudden cardiac arrest [2][3]. Different categories of arrhythmias include: Atrial fibrillation (AF): Characterized by rapid and irregular electrical activity in the atria, increasing the risk of clot formation and stroke [4]. Premature ventricular contractions (PVCs): Extra heartbeats originating from the ventricles that can give a sensation of skipped or irregular beats [5]. Ventricular tachycardia (VT): A rapid heart rhythm arising from the ventricles, which can be fatal if untreated [6]. Bradycardia: An abnormally slow heart rate, which may cause symptoms such as fatigue, dizziness, or fainting [7].

Electrocardiography (ECG) remains most widely used non-invasive method for recording and analyzing the heart's electrical activity, providing clinicians with detailed insights into cardiac performance. The analysis of ECG signals, particularly their waveform patterns and heart rate variability, is crucial for identifying various types of arrhythmias [8]. According to the Association for the Advancement of Medical Instrumentation (AAMI)[9], non-life-threatening arrhythmias can be categorized into five main classes: non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q). Figure1 shows the 5 types ofarrhythmias.

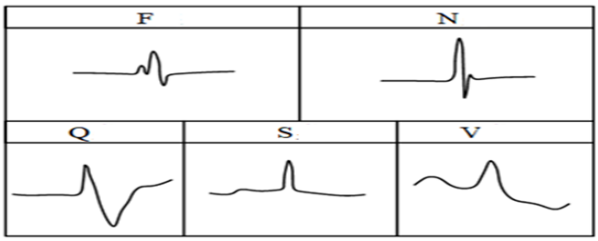


Figure 1: Arrhythmia Type

The vast amount of information captured by an ECG signal makes visual analysis by cardiologist extremely limited and indefinite. Hence, it is essential to develop computer-aided systems capable of processing and extracting parameters from ECG signals. Recent progress in wearable technology and Internet of Things (IoT) solutions has made it possible to perform continuous and extended ECG monitoring beyond conventional clinical environments [10]. These advancements have enabled the development of automated diagnostic systems that can operate efficiently even in remote or resource-limited areas. Furthermore, the adoption of machine learning and deep learning techniques has revolutionized the analysis of physiological signals, allowing complex biosignals to be processed and interpreted with greater precision, leading to valuable clinical insights[11][12]. Timely and accurate detection of arrhythmia plays a vital role in identifying cardiac disorders and improving patient outcomes through appropriate treatment. With the rapid growth of smart healthcare technologies, it is now possible to combine wearable sensors, advanced algorithms, and mobile applications to develop intelligent monitoring systems that provide continuous cardiac assessment anytime and anywhere. By employing deep learning methods for arrhythmia classification, IoT-enabled devices for real-time heart rate and ECG acquisition, and mobile platforms for data visualization, this study seeks to bridge the gap between clinical diagnosis and continuous, patient-centered monitoring.

Summary of Literature Survey and Research Gap

Electrocardiography (ECG) plays a vital role in diagnosing cardiac arrhythmias, which are irregularities in the heart's rhythm that can range from benign conditions to life-threatening episodes. Arrhythmias such as tachycardia, bradycardia, atrial fibrillation, and premature ventricular contractions (PVCs) can be detected by analyzing the morphology and timing of ECG waveforms. Over the past decade, research has increasingly focused on automated arrhythmia classification to improve diagnostic speed, accuracy, and accessibility, particularly in remote healthcare settings.Initially, most classification approaches relied on hand-crafted feature extraction from ECG signals, followed by classical machine learning classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Decision Trees [13]. While these methods provided moderate accuracy, they often failed to generalize well due to patient variability and noise interference.

With the emergence of deep learning, especially Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), researchers have shifted toward end-to-end learning frameworks. These models can extract spatial and temporal features directly from raw ECG signals, eliminating the need for manual feature engineering. For instance, Xia &Xie[14] proposed a CNN with active learning to reduce annotation requirements while maintaining high classification accuracy. Similarly, Ullah et al. [15] employed a Bi-directional LSTM (Bi-LSTM) to model long-term dependencies in ECG sequences, significantly improving classification performance.The MIT-BIH Arrhythmia Database remains the most widely used dataset for arrhythmia classification research, offering a large collection of annotated ECG recordings from multiple patients. The St. Petersburg INCART 12-lead Arrhythmia Database complements MIT-BIH by providing multi-lead recordings with diverse arrhythmia types, enabling better generalization of models. Studies like Chen et al. [16] and Li et al.[17] have demonstrated the effectiveness of CNN and hybrid CNN-LSTM models on these datasets, achieving high accuracy in offline evaluation.

In addition to dataset-based research, IoT-enabled ECG monitoring systems have emerged to bring arrhythmia detection into real-time and wearable contexts. Adil et al.[18] and Lin et al.[19] developed portable ECG systems integrated with machine learning algorithms for early arrhythmia detection. However, many such systems are limited to binary classification (arrhythmia vs. normal) and lack fine-grained categorization into clinically relevant classes such as tachycardia and bradycardia. Although several IoT-based systems support continuous ECG monitoring, many still do not incorporate deep learning models, multi-class arrhythmia classification, or real-time visualization through mobile and web applications. Recent research [20] has introduced hybrid deep learning approaches trained on both MIT-BIH and INCART datasets, showing improvements in accuracy and cross-dataset generalization. Nevertheless, the integration of these methods with practical visualization tools and user-friendly interfaces for clinical and home environments remains limited.

Research Gap

From the literature survey these are some gaps:

Real-time Multi-class Arrhythmia Detection: Many IoT-based ECG monitoring systems still emphasize binary classification, with limited capability to distinguish clinically relevant rhythms such as bradycardia and tachycardia.

Deployment of Deep Learning on Wearable Devices:Although deep learning methods show strong results in offline experiments, their real-time integration into portable, low-power IoT hardware for continuous monitoring remains underexplored.

Dataset-to-Device Transferability: Most models are trained and tested on benchmark datasets like MIT-BIH and INCART but are rarely validated on data acquired directly from real-time wearable sensors, raising concerns about generalization.

Visualization and User-Centered Design:Current solutions often lack integrated ECG waveform visualization and interactive interfaces that can support both patients and healthcare professionals in real-world use.

Research Objectives and Scope

1. To study the scope of AIOT (Artificial Intelligence of Things) system for electrocardiogram (ECG) analysis and cardiac disease detection
2. To build an integrated health monitoring system using AIOT for Arrhythmia detection.
3. To implement a wearable IoT device capable of real-time ECG signal visualization, ensuring continuous cardiac monitoring and data availability for clinical insights.

The scope of this research lies in advancing the integration of Artificial Intelligence of Things (AIoT) technologies with electrocardiogram (ECG) monitoring for early and accurate cardiac disease detection. By exploring the capabilities of AIoT, this study emphasizes not only the classification of arrhythmias through robust deep learning techniques but also the development of a practical and patient-friendly health monitoring system. The system incorporates IoT-based wearable sensors for heart signal acquisition, machine learning and deep learning models for arrhythmia detection, and a mobile application interface for accessible visualization.The scope covers three dimensions: (i) leveraging AIoT for intelligent ECG analysis, (ii) developing an integrated arrhythmia detection system for real-time health monitoring, and (iii) creating a wearable device for continuous ECG visualization and clinical data availability, thereby contributing to the future of personalized and connected healthcare.

Research Contribution

- Designing and training a customized CNN model using MIT-BIH and St. Petersburg INCART datasets for robust multi-class arrhythmia classification.
- Developing an IoT-based wearable ECG monitoring device capable of real-time ECG acquisition and classification into tachycardia, bradycardia, and normal rhythms.
- Implementing a mobile application for live ECG visualization and classification feedback to users.

This study proposes the design of an IoT-enabled ECG monitoring system that performs real-time, multi-class arrhythmia classification using optimized deep learning models. The approach will be validated on both MIT-BIH and St. Petersburg datasets and will incorporate direct waveform visualization through a dedicated mobile application.

Proposed Methodology and Results

Module 1 – Arrhythmia Classification Using MIT-BIH and St. Petersburg INCART Datasets

In this module, two ECGdatasets; MIT-BIH Arrhythmia Database and the St. Petersburg INCART 12-lead Arrhythmia Databasewere employed for the training and evaluation of classification models. Prior to analysis, the ECG signals underwent preprocessing steps such as noise removal and amplitude normalization to maintain consistency across all samples. Feature extraction was performed using both raw ECG waveforms and statistical measures derived from time- and frequency-domain techniques. A customized Convolutional Neural Network (CNN) architecture was then designed to categorize beats into five major arrhythmia classes: Normal (N), Supraventricular ectopic beats (S), Ventricular ectopic beats (V), Fusion beats (F), and Unknown beats (Q).The proposed methodology architecture is shown in Figure 2. This model's performance was compared against other deep learning and machine learning algorithms TCN, RNN, LSTM and Google-net, demonstrating superior accuracy. Comparative analysis with existing research further validated the efficiency of the proposed CNN architecture.

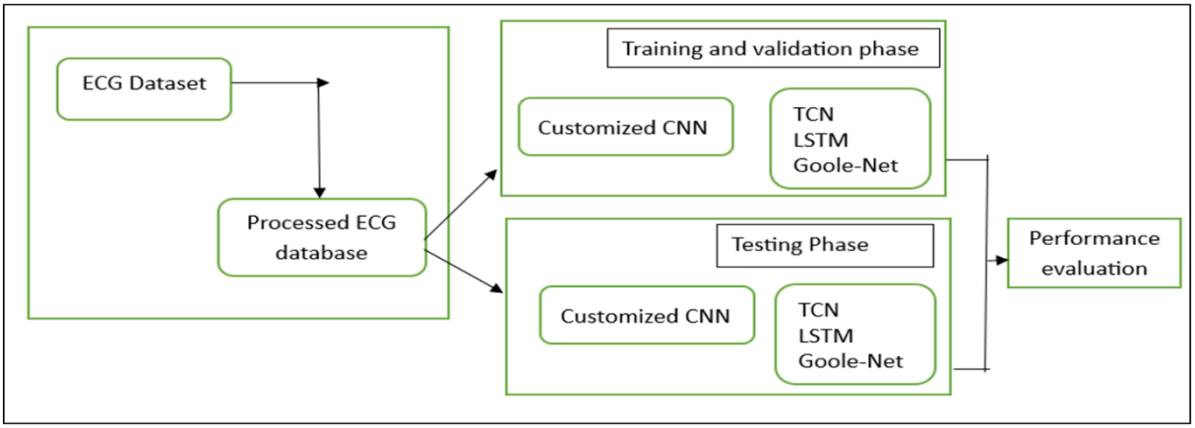


Figure 2: Proposed Methodology

Methodology

1. Data Collection

Two widely recognized ECG datasets were used in this research 1. MIT-BIH 2. St Petersburg INCAART

- MIT-BIH Arrhythmia Database :Contains 48 half-hour, two-channel ambulatory ECG recordings from 47 subjects, annotated for beat types and rhythm changes

- St. Petersburg INCART 12-lead Arrhythmia Database : Comprises 75 annotated recordings from 32 patients, each about 30 minutes long, recorded using standard clinical Holter monitoring.

These datasets were chosen for their diversity in arrhythmia types, high-quality annotations, and established use in cardiac signal classification research.

2. Preprocessing

In preprocessing to ensure signal quality and consistency: Bandpass filtering (0.5–40 Hz) was applied to suppress baseline wander and high-frequency noise. Baseline drift removal was performed using a median filter to enhance morphological clarity. Signals were normalized to a uniform amplitude range for stable model convergence. ECG beats were segmented into fixed-length windows centered on R-peaks, detected via a Pan–Tompkins algorithm.

3. Feature Extraction

Feature extraction focused on capturing both morphological (shape-based) and temporal (timing-based) information from the ECG signal. Based on prior works [21], features included:
RR Interval Features: Mean, standard deviation, and varianceof RR intervals to capture rhythm regularity. QRS Complex Features includes duration, amplitude, and slope variations for ventricular depolarization assessment.P and T Wave Morphology feature content amplitude and duration to identify atrial and repolarization abnormalities. Frequency Domain Features includes power spectral density analysis to detect changes in frequency components. Wavelet Transform Coefficients features extracted using discrete wavelet transform (DWT) for multi-resolution analysis of transient ECG patterns. Heart Rate Variability (HRV) Parameters consist of time domain and frequency domain HRV features for autonomic function assessment. These features, widely used, provide strong discriminative capability for arrhythmia classification.

4. Model Development

Three deep learning architectures were implemented:

RNN: Recurrent Neural Networks (RNNs) are particularly suited for sequential data, as they can model temporal dependencies in ECG signals by utilizing information from earlier time steps.[22].

LSTM: Long Short-Term Memory (LSTM) networks, a specialized type of RNN, use memory cells and gating units to retain long-term dependencies, thereby addressing the vanishing gradient limitations often encountered in traditional RNNs[23].

TCN: Temporal Convolutional Networks (TCNs) apply dilated causal convolutions to capture long-term temporal patterns while preserving sequence order, enabling efficient parallel processing for ECG time-series classification[24].

Layer (type)	**Output Shape**	**Param**
input_layer_10(InputLayer)	(None, 180, 1)	0
tcn (TCN)	(None,64)	144,320
dense_12 (Dense)	(None, 128)	8,320
dropout_16 (Dropout)	(None, 128)	0
dense_13 (Dense)	(None, 5)	645

Table 1Structure of TCN

The structure of TCN is shown in Table 1. The architecture of TCN is structured to start with an input layer that receives 180 ECG signal samples per beat. This step is succeeded by a stack of dilated causal convolutional layers, each comprising 64 filters and a kernel size of 5. The dilation rates increase progressively as [1, 2, 4, 8], effectively expanding the receptive field without increasing the number of layers. This configuration allows the network to integrate information from distant signal points, which is critical for modeling rhythmic dependencies in heartbeat sequences. These temporal feature representations are then propagated to a Dense layer with 128 units, followed by a Dropout layer (rate = 0.3). A final dense layer with softmax activation provides class probabilities for the five arrhythmia types. TCN is especially suited for time-series modeling, making it well-aligned with the structure and dynamics of ECG.

Google-Net: 1D-adapted Google-Net architecture, derived from the original Inception network, applies parallel convolutional kernels of multiple sizes to extract both localized and large-scale features from ECG signals [25].

Customized-CNN Model:

In the customized CNN model, handcrafted statistical features were additionally computed and fed into the auxiliary branch of the network. Handcrafted feature extraction was carried out using wavelet transform (db4). These features include 1: R-peak amplitude, 2: Beat energy, 3: Beat entropy, 4: Area under the curve (AUC), 5: Energy of detail and approximation coefficients from a 3-level wavelet decomposition this dual-input approach (raw beats + statistical features) supported the hybrid CNN architecture.Figure 3 illustrates the detailed architecture of the Hybrid CNN model, which takes as input both raw ECG signals and handcrafted features. The architecture includes convolutional and Max-pooling layers were utilized to extract features, subsequently followed by a classification layer that categorizes the signals into predefined arrhythmia classes.

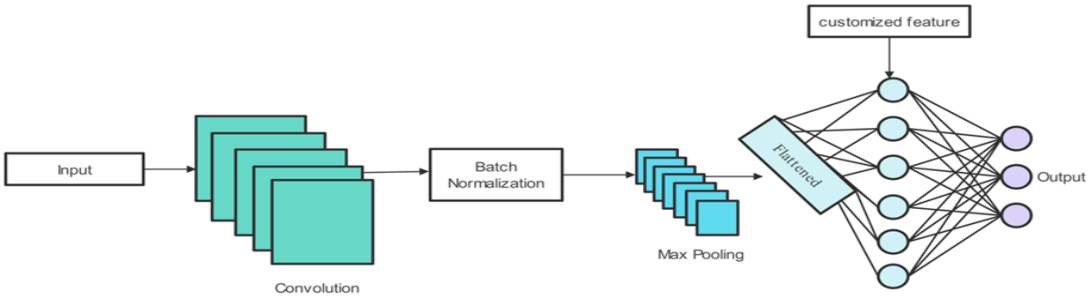


Figure 3: Proposed Custom CNN Architecture

The Hybrid CNN model integrates both raw ECG signals and handcrafted statistical features to enhance arrhythmia classification. The proposed architecture is designed with two parallel input streams. The first stream handles raw one-dimensional ECG signals, passing them through two successive convolutional layers containing 32 and 64 filters, respectively, each with a kernel size of 5. These are followed by Batch Normalization, MaxPooling1D, and Dropout layers to ensure model stability and reduce overfitting. The extracted spatial features are then flattened into a 1D representation. In parallel, the second stream processes an 8-dimensional feature vector consisting of handcrafted attributes, including statistical measures and time–frequency characteristics derived from wavelet transforms. The outputs from both streams are merged into

a single feature vector, which is processed by a Dense layer with 128 neurons, followed by a Dropout layer (rate = 0.3) for regularization, and finalized with a Dense softmax output layer containing five neurons, each representing one of the AAMI-standard arrhythmia classes. This dual-input design allows the model to effectively learn from both raw morphological information and higher-level statistical characters, thereby improving robustness, particularly when dealing with imbalanced data.The detail description is presented in Table 2.

Layer (type)	**Output Shape**	**Param #**	**Connected to**
ECG_Input (InputLayer)	(None, 180, 1)	0	-
conv1d_13 (Conv1D)	(None, 180, 128)	768	ECG_Input[0][0]
max_pooling1d_10 (MaxPooling1D)	(None, 90, 128)	0	batch_normalization_12[0]…
conv1d_14 (Conv1D)	(None, 90, 256)	98,560	dropout_37[0][0]
max_pooling1d_11 (MaxPooling1D)	(None, 45, 256)	0	batch_normalization_13[0]…
conv1d_15 (Conv1D)	(None, 45, 128)	98,432	dropout_38[0][0]
max_pooling1d_12 (MaxPooling1D)	(None, 22, 128)	0	batch_normalization_14[0]…
flatten_3 (Flatten)	(None, 2816)	0	dropout_39[0][0]
Feature_Input (InputLayer)	(None, 4)	0	-
concatenate_4 (Concatenate)	(None, 2820)	0	flatten_3[0][0], Feature_Input[0][0]
dense_26 (Dense)	(None, 128)	361,088	concatenate_4[0][0]
dense_27 (Dense)	(None, 64)	8,256	dropout_40[0][0]
Output (Dense)	(None, 5)	325	dropout_41[0][0]
Total params: 569,477 (2.17 MB) **Trainable params:** 568,453 (2.17 MB) **Non-trainable params:** 1,024 (4.00 KB			

Table 2. Structure of Customized Convolutional Neural Network Model (CNN)

Results:

Deep Learning models	Train Accuracy	Train Loss	Val Accuracy	Val Loss	Precision	Recall	F1 Score	Testing Accuracy
CNN	98.90	0.031	98.85	0.034	98	98	98	98.87
RNN	83.58	0.58	83.29	0.59	77	83	78	83.44
TCN	97.67	0.08	97.79	0.086	98	98	98	98.15
LSTM	97.71	0.08	97.73	0.08	98	98	98	97.98
Google-Net	97.74	0.076	97.71	0.085	98	98	98	97.80

Table 3. Result summary of Deep Learning Model on MIT-BIH dataset

Deep Learning models	Train Accuracy	Train Loss	Val Accuracy	Val Loss	Precision	Recall	F1 Score	Testing Accuracy
CNN	89.33	0.257	89.18	0.259	88	87	87	89.32
RNN	88.31	0.35	88.57	0.34	88	87	87	88.31
TCN	98.52	0.0561	98.58	0.048	99	99	99	98.49
LSTM	98.76	0.041	98.65	0.043	99	99	99	98.74
Google-Net	99.19	0.025	98.10	0.068	99	99	99	98.11

Table 4. Result summary of Deep Learning Model on St-Petersburg INCART dataset

Deep Learning models	Train Accuracy	Train Loss	Val Accuracy	Val Loss	Precision	Recall	F1 Score	Testing Accuracy
Customized CNN MITBIH	99.19	0.03	98.90	0.04	99	99	99	**99.10**
Customized CNN st petersburg	98.56	0.049	98.71	0.051	99	99	99	**98.71**

Table 5. Customized CNN Result on MIT-BIH and St. Petersburg dataset

The experimental results clearly indicate that the proposed customized CNN architecture outperformed all other evaluated deep learning models, including RNN, LSTM, TCN, and Google-Net. While each of these models demonstrated strong performance in ECG arrhythmia classification, the customized CNN consistently achieved higher accuracy across both training and testing phases. This improvement can be attributed to its dual-input design, which effectively integrates raw ECG waveform information with statistical features, enabling more precise feature representation and enhanced discriminative capability. The superior accuracy of the customized CNN not only demonstrates its robustness in handling complex ECG patterns but also validates its suitability for real-time arrhythmia detection tasks when compared to conventional deep learning architectures. Table 3,4,5 shows the accuracy measure summary of deep learning classifier with customized CNN

Author	**Model**	**Accuracy**
Hannun et al.	CNN (DNN)	97.0%
Evren et al.	Memory-enhanced artificial hummingbird algorithm	98.87
Kumar et al.	Fuzzy clust-net	98.66
Ray et al.	Deep LSTM	98.00
Roger et al.	Auto-encoder LSTM	98.57
Cong zho et al.	Bidirectional gated recurrent units (BiGRU)	98.70
Yu-Jin Lin1 et al.	CNN + Decision tree	94.96%.
Customized CNN	Customized CNN+ Handcrafted feature	99.10

Table 6. Comparative Performance Analysis of Customized CNN with Previous Research: on MIT-BIH

Author	Model	Accuracy
Zhao et al.	TCN + attention	94.3%
Rahman et al.	Feature Extraction + TCN	93%
Chauhan & Gupta	Deep Neural Network + ML	94.1%
Ponemash et al.	Hybrid handcrafted + deep learning features	96.2%
Customized CNN	**Customized CNN+ Handcrafted feature**	**98.71%**

Table 7. Comparative Performance Analysis of Customized CNN with Previous Research: on St-Petersburg INCART dataset

A comparative analysis with prior research on the MIT-BIH and St. Petersburg INCART datasets further validates the effectiveness of the proposed customized CNN. Table 6 and Table 7 represent comparative performance analysis with related work with customized CNN. Previous studies employing conventional CNNs, hybrid CNN-RNN models, or lightweight architectures have reported commendable accuracies; however, their performance often stabilized due to limitations in feature representation or dataset-specific tuning. In contrast, the customized CNN developed in this study achieved superior accuracy, surpassing the reported benchmarks from earlier works. This improvement is primarily due to its dual-input architecture that combines raw ECG waveforms with handcrafted statistical features, enabling more comprehensive pattern recognition. The results highlight that the proposed approach not only advances the state-of-the-art in arrhythmia classification but also offers a robust framework adaptable to diverse ECG datasets.

Module 2 – Heart Rate-Based Arrhythmia Detection

The second module of the proposed system focuses on heart rate driven rhythm analysis for real-time arrhythmia detection. In this module, a heart rate sensor was used to gather physiological data from 19 persons. The recorded heart rate values were analyzed and categorized into three groups: bradycardia (abnormally slow heart rate), normal rhythm, and tachycardia (abnormally fast heart rate). For adults at rest, a normal heart rate typically falls between 60 and 100 beats per minute (BPM), reflecting stable cardiac activity under standard conditions. Rates below 60 BPM

are classified as bradycardia, while those exceeding 100 BPM are identified as tachycardia [26]. Table 8 summarizes the threshold values used to differentiate these conditions. The classification task was carried out using four widely recognized machine learning techniquesLogistic Regression, Random Forest, k-Nearest Neighbors (k-NN), and Support Vector Machine (SVM)to ensure a reliable performance comparison. Additionally, this module supports live data acquisition, continuously tracking a person's pulse in real time and instantly categorizing it into the appropriate rhythm class. Through the integration of continuous monitoring and automated analysis, the system aids in the early recognition of abnormal heart rate patterns, which is essential forpreventive healthcare and timely medical attention

Figure 4: Heart Rate system Architecture

Figure4 shows the system architecture. The heart rate sensor is placed on the user's fingertip, where it detects changes in blood volume by analyzing light absorption variations and produces an analog voltage signal for each heartbeat. This signal is fed into the NodeMCU microcontroller via its ADC pin. The cleaned signal is then used to calculate the heart rate in beats per minute (BPM). These BPM values are wirelessly transmitted through the ESP8266's built-in Wi-Fi module for subsequent processing. The collected time-series data is categorized into three rhythm classesnormal, bradycardia, and tachycardiausing machine learning models. This setup allows continuous heart rate tracking in real time and supports remote monitoring for clinical evaluation.

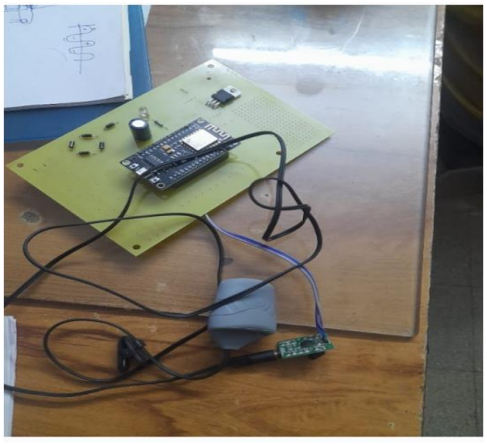
Rhythm type	**Heart rate threshold value**
Normal	60< = HR < = 100(BPM)
Bradycardia	HR < = 60(BPM)
Tachycardia	HR > = 100(BPM)

Table 8. Heart RateThreshold value

Classifier	Accuracy
Logistic Regression	99.00%
Support Vector Machine	98.28%
Random Forest	99.20%
K-nearest Neighbor	98.33%

Table 9. Classifier accuracy on Heart Beat data

Classifier accuracy on BPM data is shown in Table 9. The results evaluated by Logistic Regression and Random Forest classifiers 99.00%, 99.20%, indicating their strong capability in correctly classifying heart rate patterns. The SVM classifier also exhibited high accuracy (98.28%), effectively handling non-linear reparability in the BPM dataset. The KNN classifier recorded an accuracy of 97.76%, slightly lower than the others, likely due to its sensitivity to the value of k and the distribution of neighboring data points. Along with above result the proposed system integrates a heart rate sensor with an IoT-enabled mobile application to provide continuous, real-time monitoring of cardiac activity. The sensor captures heart rate signals from the user and transmits the data to the mobile app, where it is instantly processed and analyzed. Based on predefined clinical thresholds, the app classifies the heart rhythm into three categories: bradycardia , normal rhythm, and tachycardia. This real-time classification ensures that users can immediately identify abnormal heart activity and take appropriate action. The mobile app also provides a user-friendly interface for live visualization of heart rate trends, allowing patients andhealthcare providers to track rhythm fluctuations over time. Figure 5 shows the heart rate IOT module to capture and analyze the heart rate data.



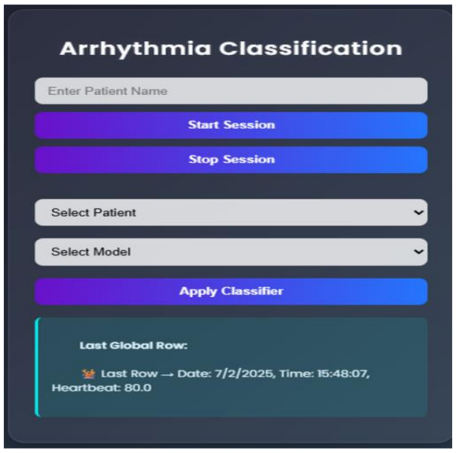


Figure 5: Heart rate IOT module

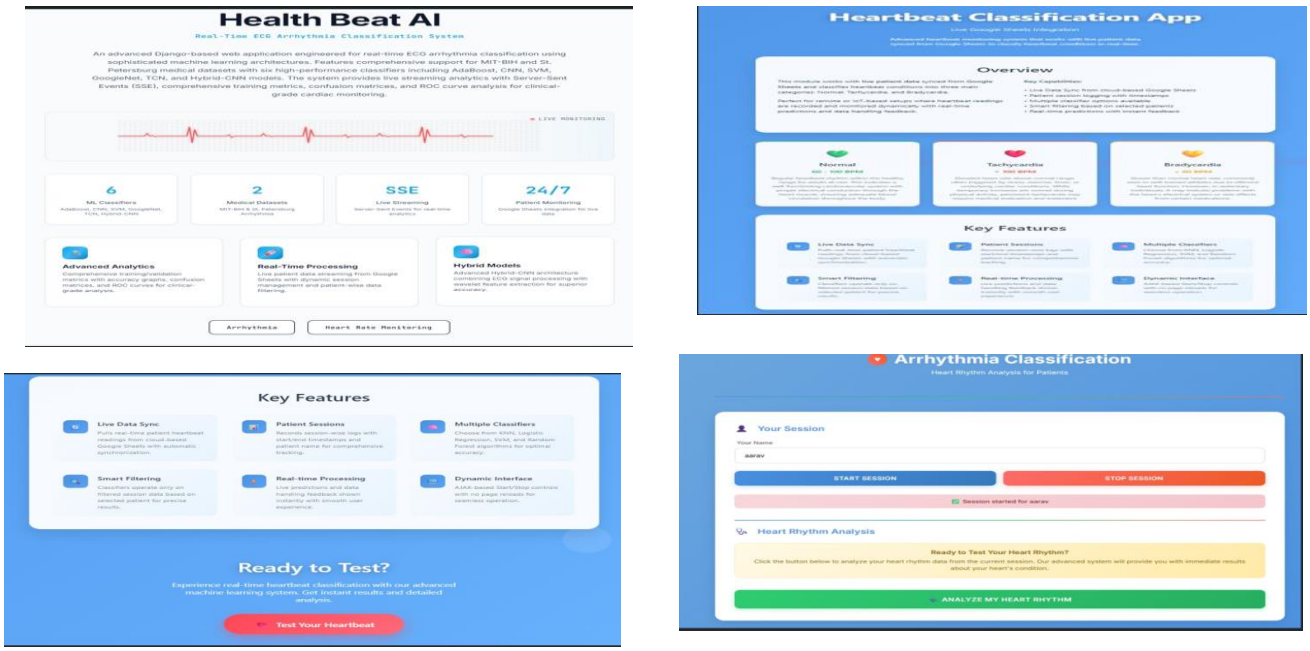


Figure 6: Heart rate monitoring system app

Figure 6 presents an overview of the heart rate monitoring application, where each user is uniquely identified through a session ID, and the system displays live heart rate measurement results.

Module 3 – Real-Time ECG Signal Acquisition and Visualization

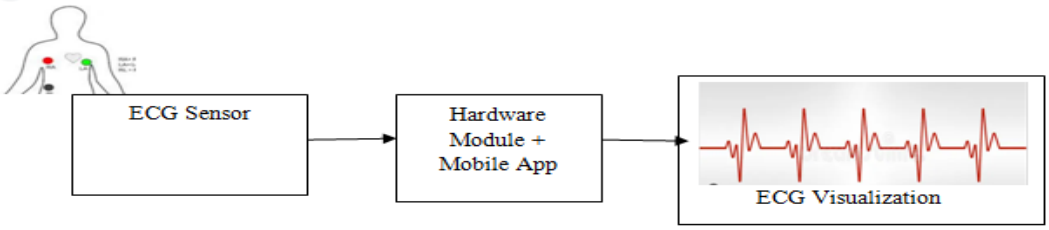


Figure 7. ECG system Structure

In this ECG system module, an ECG sensor hardware unit along with an application program was used for real-time ECG visualization through the mobile application. The details of this implementation are illustrated in Figure 7.In this module, a portable ECG sensor(AD8232 ECG sensor) was employed to capture real-time cardiac signals directly from subjects. The acquired signals were transmitted to the processing unit and displayed on a mobile application, providing an intuitive visualization of the user's cardiac activity. This setup enables continuous monitoring

of the electrical activity of the heart, allowing clinicians and users to observe waveform morphology in real time. The details of setup is shown in Figure 9 and ECG visualization output is shown in figure 8. The system not only enhances patient engagement by offering immediate feedback but also supports preliminary cardiac assessment outside clinical environments, thereby demonstrating the feasibility of integrating ECG sensing into wearable IoT-based health monitoring platforms.

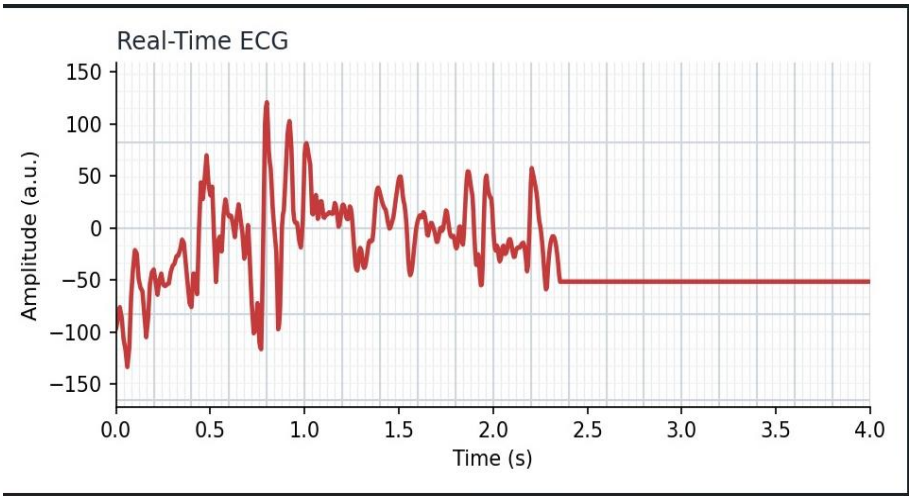


Figure 8: ECG visualization

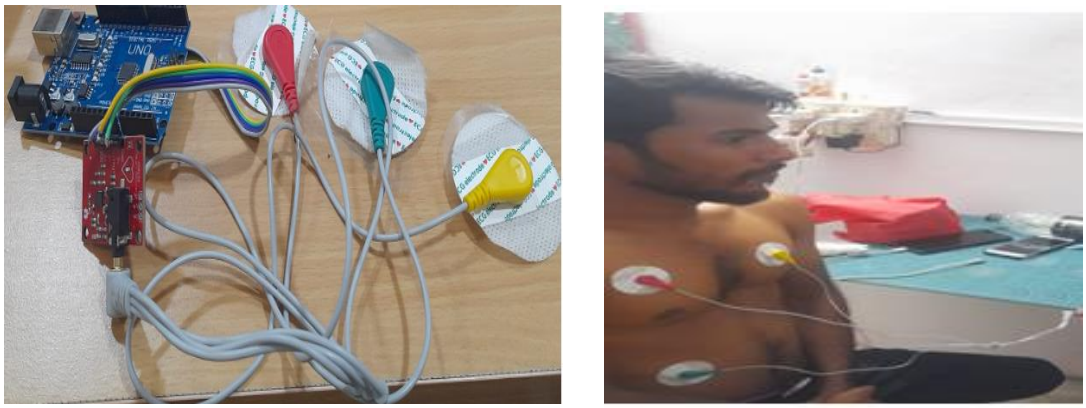


Figure 9: ECG system

To enhance the system's functionality beyond visualization, a data storage feature was incorporated. Each recorded ECG session can be securely stored in the application's database under a unique session ID, ensuring that individual records are properly managed and retrievable for future reference. This dual functionality of real-time monitoring and persistent storage not only enables immediate assessment of cardiac rhythms but also facilitates longitudinal tracking of heart health, supporting clinical analysis and patient history management.

Conclusion

This research successfully addressed the challenge of automated arrhythmia detection and real-time ECG monitoring through a three-module system. In the first module, standard datasets such as MIT-BIH and St. Petersburg INCART were utilized to design and assess multiple deep learning models, including RNN, LSTM, TCN, and GoogleNet, with performance compared against a customized CNN. The developed hybrid CNN achieved the highest accuracy, surpassing the other architectures as well as results reported in earlier studies. The second module involved the development of a heart rate monitoring framework using a hardware sensor, where classification of rhythms into bradycardia, normal, and tachycardia was carried out through algorithms like Logistic Regression, Random Forest, KNN, and SVM. This system was integrated with a mobile application to deliver real-time visualization, allowing continuous monitoring and analysis of cardiac activity. The third module centered on ECG signal collection using an IoT-based sensor, enabling real-time waveform display on a mobile platform. This functionality extends ECG tracking beyond hospital settings and supports continuous patient observation.Together, these modules form a robust framework for arrhythmia detection, combining dataset-driven deep learning approaches with real-time IoT-based monitoring and visualization. The system demonstrates significant potential for use in telemedicine, remote patient monitoring, and personal healthcare applications.

Future research may extend the system to support multi-class arrhythmia detection in real time, covering a wider range of clinically relevant abnormalities. optimizing the models for lightweight deploymenton low-power wearable hardware will improve portability and usability

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